Abstract

Detecting prestressed wire breakage in concrete bridges is essential for ensuring safety, longevity, and preventing catastrophic failures. Aging infrastructure is particularly vulnerable to such damage, often accelerated by environmental and operational factors. Prestressed wire breakage, occurring within inner sections of structures, remains undetectable by conventional methods, highlighting the urgent need for innovative approaches. Conventional structural health monitoring (SHM) techniques, such as visual inspections and strain sensing, often fail to detect early-stage internal damages, are time-consuming, and costly. These limitations highlighted the need for advanced and automated methods for timely damage detection. Advances in acoustic event detection (AED) and artificial intelligence (AI)-based models provide substantial potential to transform monitoring methods by enabling precise, automated identification of events, particularly wire breakage.

This research aims to design and validate advanced automated models for AED to monitor wire breakages and other operational events in prestressed concrete bridges. The approach consists of two primary components. First, advanced signal processing techniques, including Short-Time Fourier Transform (STFT), Log-STFT, Mel-Frequency Cepstral Coefficients (MFCC), Persistence Spectrum (PS), and Hilbert-Huang Transform (HHT), are employed to extract meaningful features from AE signals and convert them into spectrum images suitable for model training. Each representation captures different signal characteristics in time and frequency domains, contributing different information for model learning. Second, state-of-the-art deep learning (DL) models, including Artificial Neural Networks (ANNs) and pretrained convolutional neural network (CNN) architectures enhanced with Bottleneck Attention Mechanisms (BAM), are utilized to detect and classify signals generated by different sources (wire breakage, environmental noise, hammering, etc.). Furthermore, a novel hybrid model, AcousticNet, was designed specifically for acoustic event classification in SHM. AcousticNet integrates dilated convolutional

layers, gated recurrent units, and channel-spatial attention layers tailored to AE signal characteristics. Besides, data scarcity, a critical challenge in DL approaches, was addressed using Generative Adversarial Networks (GANs) and their variants. A custom GAN model, STFTsynth, was developed to generate realistic spectrograms, enhancing model robustness and generalization capabilities. These models were trained and validated on extensive datasets collected from controlled laboratory experiments and in situ bridge monitoring scenarios, ensuring adaptability and generalization ability.

Comprehensive analysis indicated that the Xception model, enhanced with BAM, and the proposed AcousticNet significantly outperformed other architectures in capturing intricate acoustic signal patterns. These models demonstrated exceptional performance in detecting and classifying acoustic events, validating the potential of DL in SHM. Across all experiments, AcousticNet consistently demonstrated superior performance in event detection tasks under diverse conditions. It could achieve an F1-score of 83.18% using log-STFT spectrograms and outperforming the robust Xception+BAM model. Moreover, STFTsynth effectively generated realistic spectrograms, as confirmed by visual inspection and consistently low Fréchet Inception Distance (FID) scores across most scenarios, demonstrating its strong potential to enhance training diversity and improve model accuracy.

This research represents a substantial advancement in the automated monitoring of prestressed concrete bridges. Unlike the conventional SHM approaches using static spectrograms, this study integrates dynamic signal representation and synthetic data augmentation to improve models' performance. These integrated methodologies effectively address data scarcity and improve classification accuracy, providing a robust, real-time, non-invasive monitoring framework. The proposed methods can potentially improve early damage detection, reduce the risk of catastrophic failures, and demonstrate applicability in real-world scenarios. These advancements contribute significantly to SHM and establish a foundation for future AI-driven infrastructure monitoring systems, promoting safer and more resilient structures worldwide.